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Emotion Recognition through Physiological Signals for Human-Machine Communication

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Abstract

The ability to recognize emotion is one of the hallmarks of emotion intelligence. This paper proposed to recognize emotion using physiological signals obtained from multiple subjects. IAPS (International Affective Picture System) images were used to elicit target emotions. Five physiological signals: Blood volume pulse (BVP), Electromyography (EMG), Skin Conductance (SC), Skin Temperature (SKT) and Respiration (RESP) were selected to extract 30 features for recognition. Two pattern classification methods, Fisher discriminant and SVM method are used and compared for emotional state classification. The experimental results indicate that the proposed method provides very stable and successful emotional classification performance as 92% over six emotional states.

1 Introduction

One of the interesting challenges in the community of human-computer interaction today is how to make computers be more human-like for intelligent user interfaces. In several experiments of Reeves and Nass [1], they show that humans impose their interpersonal behavioral patterns onto their computers. Thus, the design of recent human-computer interfaces should reflect this observation in order to facilitate more natural and more human-like interaction. Emotion, one of the user affect, has been recognized as one of the most important ways of people to communicate with each other. Given the importance and potential of the emotions, affective interfaces using the emotion of the human user are gradually more desirable in intelligent user interfaces such as human-robot interactions [2]. In order for such an affective user interface to make use of user emotions, the emotional state of the human user should be recognized or sensed in many ways from diverse modality such as facial expression, speech, and gesture. Thus, this paper investigates the automatic recognition of emotions in human-machine interaction using the combination of several feature sets from physiological signals. Research efforts in human-computer interaction are focused on the means to empower computers (robots and other machines) to understand human intention, e.g. speech recognition and gesture recognition systems [3]. In

spite of considerable achievements in this area during the past several decades, there are still a lot of problems, and many researchers are trying to solve them. Besides, there is another important but ignored mode of communication that may be important for more natural interaction: emotion plays an important role in contextual understanding of messages from others in speech or visual forms.
There are numerous areas in human-computer interaction that could effectively use the capability to understand emotion [3]. For example, it is accepted that emotional ability is an essential factor for the next-generation personal robot, such as the Sony AIBO [4]. It can also play a significant role in 'intelligent room' [5] and 'affective computer tutor' [6]. The remainder of this paper is organized as follows: First, we describe related works to recognize the emotions of human user. The experience protocol and used equipment for emotion recognition are presented in section 3. In section 4, we specify the feature extraction method to classify our emotional categories from physiological signals. In section 5, we present the obtained experimental results. Finally, conclusion and future works are presented in section 6.

2 Related work

2.1 Modeling of discrete emotions

As people display the emotional expressions of others to their various degrees individually, it is not an easy task to judge or to model human emotions. The researchers often use two different methods to model emotions. One approach is to label the emotions in discrete categories, i.e. human judges have to choose from a prescribed list of word labels, e.g. joy, sadness, surprise, anger, love, fear, etc. One problem with this method is that the stimuli may contain blended emotions that cannot adequately be expressed in words since the choice of words may be too restrictive and culturally dependent. Another way is to have multiple dimension or scales to categorize emotions. Instead of choosing discrete labels or words, observers can indicate their impression of each stimulus on several continuous scales, for example, pleasant-unpleasant, attention-rejection, simple-complicated, etc. Two common scales are valence and arousal. Valence represents the pleasantness of stimuli, with positive (or pleasant) on the end, and negative (or unpleasant) on the other. Another dimension is arousal (activation level). The different emotional labels could be plotted at various positions on a two-dimensional plane spanned by these two axes to construct a 2D emotion model [7].
Recently, the low consistency of physiological configurations supported the hypothesis that the autonomic nervous system ANS activation during emotions indicates the demands of a specific action tendency and action disposition, instead of reflecting emotions [8].
The relation between physiological signals and arousal/valence is established in psychophysiology that argues that the activation of the autonomic nervous system (ANS) changes while emotions are elicited [9].

2.2 Automatic emotion recognition using physiological signals

There is a vast body of literature on the automatic recognition of emotions. With labelled data collected from different modalities, most studies rely on supervised pattern classification approaches to automatic emotion recognition.

Relatively little attention has been paid so far to physiological signals for emotion recognition compared to other channels of expression. A significant series of work has been conducted by Picard and colleagues at MIT Lab. For example, they showed that certain affective states may be recognized by using physiological measures including heart rate, skin conductivity, temperature, muscle activity, and respiration velocity [10]. Eight emotions deliberately elicited from a subject in multiple weeks were classified with an overall accuracy of 81%. Nasoz and al. [11] used movie clips to elicit target emotions from 29 subjects and achieved the best recognition accuracy (83%) by applying the Marquardt Backpropagation algorithm. More recently, Wagner and al [12] presented an approach to the recognition of emotions elicited by music using 4-channel biosignals which were recorded while the subject was listening to music songs, and reached an overall recognition accuracy of 92% for a 4-class problem.

3. Experimental Data Acquisition

3.1 Emotion induction protocol

A prevalent method to induce emotional processes consists of asking an actor to feel or express a particular mood. This strategy has been widely used for emotion assessment from facial expressions and to some extent from physiological signals [13]. However, even if actors are known to deeply feel the emotion they try to express, it is difficult to insure physiological responses that are consistent and reproducible by nonactors. Furthermore, emotions from actor-play databases are often far from real emotions found in everyday life.

The alternate approach for inducing emotions is to present particular stimuli to an ordinary participant. Various stimuli can be used such as images, sounds, videos [14] or video games. This approach presents the advantages that there is no need for a professional actor and that responses should be closer to the ones observed in real life.

It was essential to obtain a database of physiological signals representing specific emotional statuses. To acquire a database of physiological signals in which the influence of emotional status was faithfully reflected, we developed a set of elaborate protocols for emotion induction. We use the international affective picture system (IAPS) developed by LANG et al [15], and adopted for many psychophysiological studies involving emotion induction.

A preliminary test of the protocols was performed for 10 healthy subjects (7 males, 3 females) aged from 23 to 30 years. We have used five physiological signals (Blood Volume Pulse (BVP), Electromyography (EMG), Electrodermal activity (SC), Skin temperature (SKT) and Respiration (Resp)) (Figure 1). The EMG was measured from frontalis muscle. BVP and SKT were measured from little finger and the ring finger of the left hand, respectively. SC was measured from the index and middle fingers of the right hand. Resp was measured from abdomen subject's. We used a combination of these signals, to derive a set of features that can be used to train a classification algorithm.

For each subject, we presented six basic emotions: Amusement, Contentment, Disgust, Fear, No emotion (Neutrality) and Sadness. For each emotion, ten images are presented during 50 seconds.

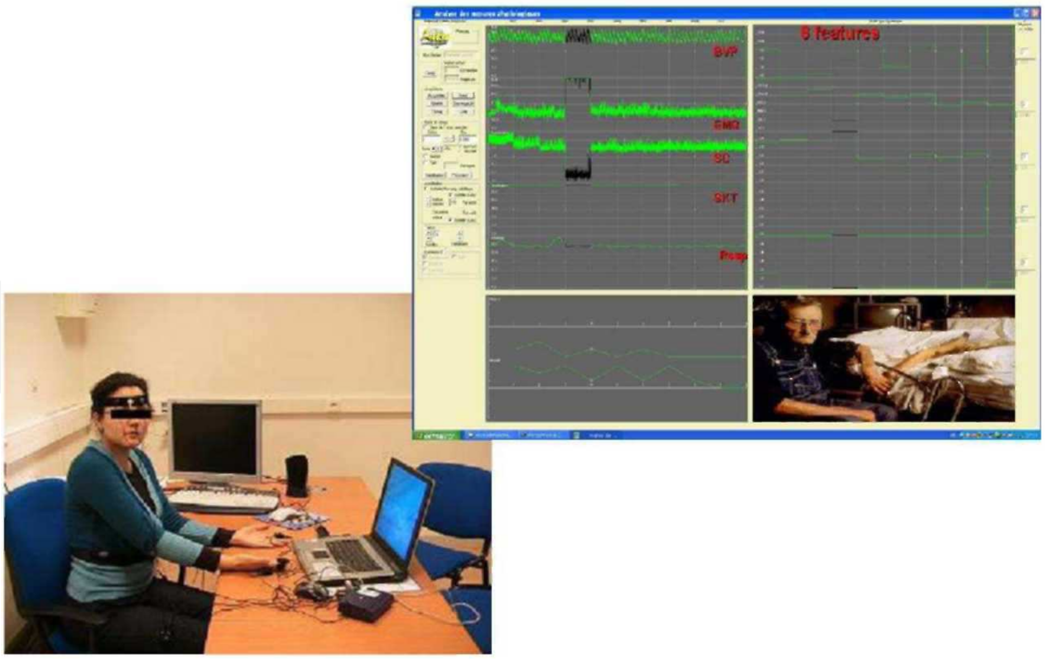

Fig. 1. Physiological signals acquisition system

3.2 Acquisition of physiological signals

The physiological signals were acquired using the PROCOMP Infiniti system [16]. The sampling rate was fixed at 256 samples per second for all the channels. Appropriate amplification and bandpass filtering were performed. One session of experiments took approximately 5 min. The subjects were requested to be as relaxed as possible during this period. Subsequently, emotional stimulus was applied, and physiological signals were recorded.

The participant was asked to self assess the valence and the arousal of his/her emotion using a Self Assessment Manikin (SAM [17]), with 9 possible numerical judgments for each dimension (arousal and valence), which will be used in future works. The used sensors are described in the following.

3.2.1 Blood Volume Pulse (BVP)

The Blood Volume pulse sensor uses photoplethysmography to detect the blood pressure in the extremities. Photoplethysmography is a process of applying a light source and measuring the light reflected by the skin. At each contraction of the heart, blood is forced through the peripheral vessels, producing engorgement of the vessels under the light source-thereby modifying the amount of light to the photosensor. The resulting pressure waveform is recorded.

Fig. 2. BVP sensor

3.2.2 Electromyography (EMG)

The electromyographic sensors measure the electromyographic activity of the muscle (the electrical activity produced by a muscle when it is being contracted), amplify the signal and send it to the encoder. In the encoder, a band pass filter is applied to the signal. For all our experiments, the sensor has used the 0-400 microvolt range and the 20-500 Hz filter, which is the most commonly used position. (Figure 3)

Fig. 3. EMG sensor

3.2.3 Electrodermal activity (EDA)

Electrodermal activity (EDA) is another signal that can easily be measured from the body surface and represents the activity of the autonomic nervous system. It is also called galvanic skin response [18]. It characterizes changes in the electrical properties of the skin due to the activity of sweat glands and is physically interpreted as conductance. Sweat glands distributed on the skin receive input from the sympathetic nervous system only, and thus this is a good indicator of arousal level due to external sensory and cognitive stimuli.

Fig. 4. Skin Conductivity sensor

3.2.4 Skin Temperature (SKT)

Variations in the skin temperature (SKT) mainly come from localized changes in blood flow caused by vascular resistance or arterial blood pressure. Local vascular resistance is modulated by smooth muscle tone, which is mediated by the sympathetic nervous system. The mechanism of arterial blood pressure variation can be described by a complicated model of cardiovascular regulation by the auto-nomic nervous system. Thus it is evident that the SKT variation reflects autonomic nervous system activity and is another effective indicator of emotional status.

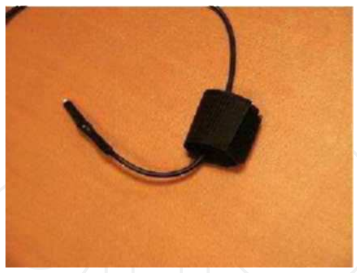

Fig. 5. Skin Temperature sensor

3.2.5 Respiration (Resp)

The respiration sensor can be placed either over the sternum for thoracic monitoring or over the diaphram for diaphragmatic monitoring (Figure 6). The sensor consists mainly of a large velcro belt which extends around the chest cavity and a small elastic which stretches as the subject's chest cavity expands. The amount of stretch in the elastic is measured as a voltage change and recorded. From the waveform, the depth the subject's breath and the subject's rate of respiration can be learned.

Fig. 6. Respiration sensor

4. Features extraction

Having established a set of signals which may be used for recognizing emotion, it is then necessary to define a methodology in order to enable the system to translate the signals coming from these sensors into specific emotions. The first necessary step was the extraction of useful information bearing features for pattern classification.

For emotion recognition training or testing, the features of each bio-potential data must be extracted. In this study, for each record, we compute the six parameters proposed by Picard [10] on the N values (5 seconds at 256 samples per second gives N=1280): the mean of the raw signals (Eq.1), the standard deviation of the raw signals (Eq.2), the mean of the absolute values of the first differences of the raw signals (Eq.3), the mean of the absolute values of the first differences of the normalized signals (Eq.4), the mean of the absolute values of the second differences of the raw signals (Eq.5) and the mean of the absolute values of the second differences of the normalized signals (Eq.6).

$$\mu_x = \frac{1}{T}\sum_{t=1}^{T} X(t) = \bar{X}(t) \quad (4.1)$$

$$\sigma_x = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(X(t)-\mu_x)^2} \quad (4.2)$$

$$\delta_x = \frac{1}{T-1}\sum_{t=1}^{T-1}|X(t+1)-X(t)| \quad (4.3)$$

$$\bar{\delta}_x = \frac{1}{T-1}\sum_{t=1}^{T-1}|\bar{X}(t+1)-\bar{X}(t)| = \frac{\delta_x}{\sigma_x} \quad (4.4)$$

$$\gamma_x = \frac{1}{T-2}\sum_{t=1}^{T-2}|X(t+2)-X(t)| \quad (4.5)$$

$$\bar{\gamma}_x = \frac{1}{T-2}\sum_{t=1}^{T-2}|\bar{X}(t+2)-\bar{X}(t)| = \frac{\gamma_x}{\sigma_x} \quad (4.6)$$

where t is the sampling number and T is the total number of sample.

5. Emotion recognition method

5.1 Classification methods

After having extracted the features as described in the previous section, we then trained a statistical classifier, with the goal of learning the corresponding emotion for a set of features with which it is presented. A number of different classification algorithms have been proposed in the literature, Fernandez [19] for example used HMMs, while Healey [20] used Fisher linear discriminant projection. This paper will focus its attention on two of them: SVM algorithm and the Fisher linear discriminant. We chose to test and compare both methods. Feature vectors extracted from multiple subjects under the same emotional stimulus form a distribution in high-dimensional space.

- In SVM method and without dimensionality reduction, our system directly gives extracted feature vectors to the support vector machine (SVM) classifier.

-In the 2nd method, we reduce the dimension of the feature vector by Fisher projection and we use subsequent quadratic classifier for recognition.

Both methods will be now briefly described.

5.2 Support vector machine

Machine learning algorithms receive input data during a training phase, build a model of the input and output a hypothesis function that can be used to predict future data. Given a set of labeled training examples

$$S = ((x_1,y_1),\ldots,(x_l,y_l)), y_i \in \{-1,1\} \quad (5.1)$$

learning systems typically try to find a decision function of the form

$$h(x) = \mathrm{sgn}(\langle w.x\rangle + b)) \quad (5.2)$$

that yields a label $e\{-1,1\}$ (for the basic case of binary classification) for a previously unseen example x. Support Vector Machines are based on results from statistical learning

theory, pioneered by Vapnik [21], instead of heuristics or analogies with natural learning systems.
SVM algorithms separate the training data in feature space by a hyperplane defined by the type of kernel function used. They find the hyperplane of maximal margin, defined as the sum of the distances of the hyperplane from the nearest data point of each of the two classes. The size of the margin bounds the complexity of the hyperplane function and hence determines its generalization performance on unseen data. The SVM methodology learns nonlinear functions of the form:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l}\left(\alpha_i y_1 K(x_i x) + b\right)\right) \tag{5.3}$$

where the α_i are Lagrange multipliers of a dual optimization problem. Once a decision function is obtained, classification of an unseen example x amounts to checking on what side of the hyperplane the example lies.

5.3 Fisher linear discriminant

The Fisher's discriminant is a technique used to reduce a high dimensional feature set, x, to a lower dimensional feature set y, such that the classes can be more easily separated in the lower dimensional space. The Fisher discriminant seeks to find the projection matrix w such that when the original features are projected onto the new space according to

$$y = w^t x, \tag{5.4}$$

the means of the projected classes are maximally separated and the scatter within each class is minimized. This matrix w is the linear function for which the criterion function:

$$J(w) = \frac{w^t S_B w}{w^t S_W w} \tag{5.5}$$

is maximized. In this equation, S_B and S_W represent the between class scatter and within class scatter, respectively. This expression is well known in mathematical physics as the generalized Rayleigh quotient. This equation can be most intuitively understood in the two class case where is reduces to:

$$J(w) = \frac{\tilde{m}_1 - \tilde{m}_2}{\tilde{s}_1^2 + \tilde{s}_2^2} \tag{5.6}$$

where $\tilde{m}_1$ and $\tilde{m}_2$ are the projected means of the two classes and $\tilde{s}_1$ and $\tilde{s}_2$ are the projected scatter of the two classes. This function is maximized when the distance between the means of the classes is maximized in the projected space and the scatter within each class is minimized [22].

6. Experimental results

Figure 7 shows an example of the five physiological signals recorded during the induction of six emotions (Amusement, Contentment, Disgust, Fear, Neutrality and Sadness) for subject1 (male) and subject2 (female), respectively. It can be seen that each physiological signal, varies widely across emotion and also across subjects.

For emotion recognition, we have implemented the SVM method with a linear kernel and Fisher's discriminant classifier. A set of six examples for each basic emotion was used for training, followed by classification of 4 unseen examples per emotion.
Table 1 gives the percentage of correctly classified examples for ten subjects using SVM method and Fisher's discriminant. Using a linear classifier, we are able to correctly classify 6 emotions of 10 subjects.As it can be observed, Fisher and SVM classifiers give a good results (92%, 90% respectively) for emotion recognition.

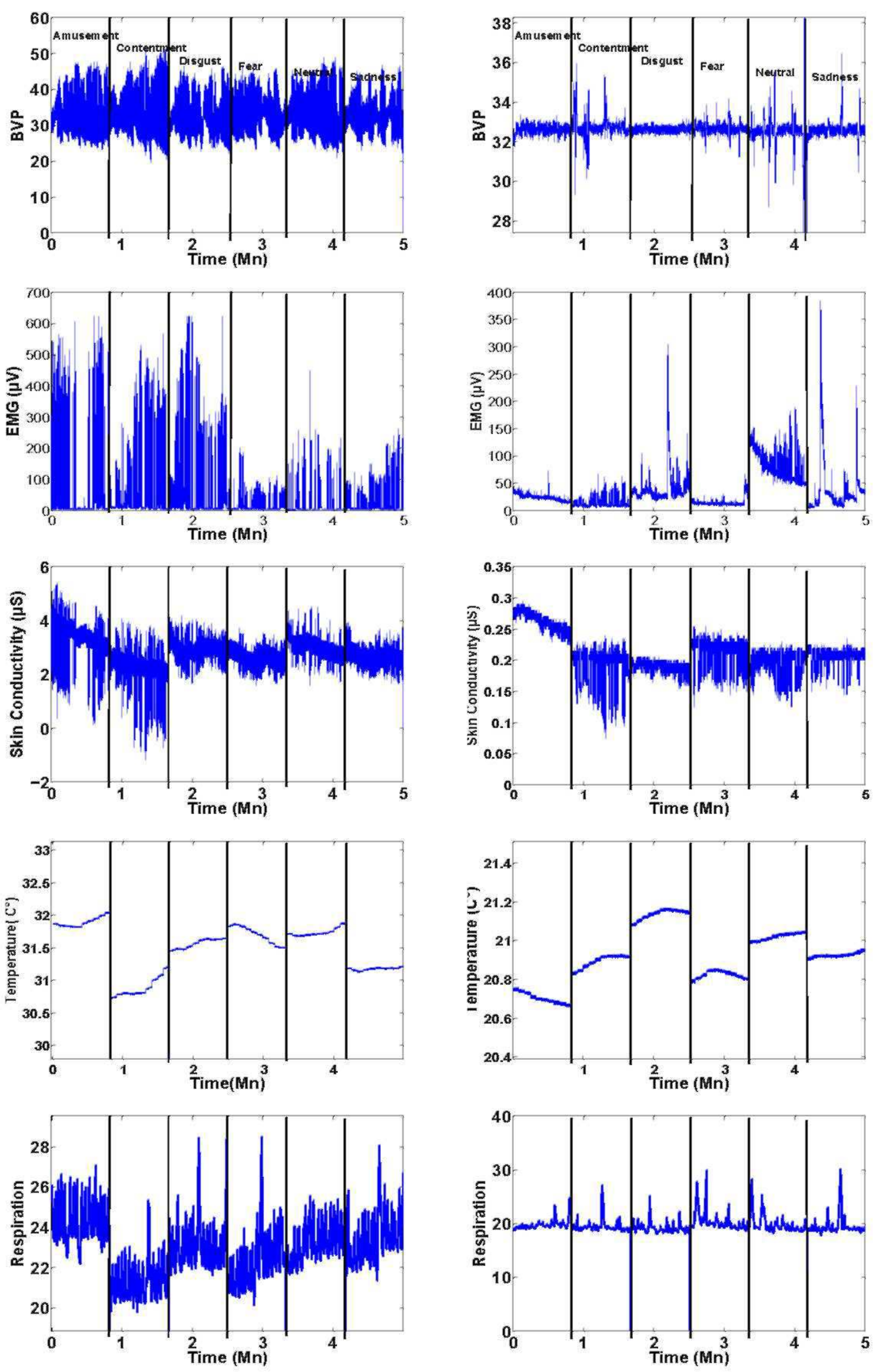

Fig. 7. An example of five physiological signals (BVP, EMG, SC, SKT and Resp) acquired during the induction of the six emotions (left: Subjectl, right: Subject 2)

Subject	Fisher Discriminant	SVM (linear kernel)
Subject1	90%	100%
Subject2	100%	90%
Subject3	100%	90%
Subject4	100%	90%
Subject5	100%	90%
Subject6	80%	90%
Subject7	80%	90%
Subject8	90%	80%
Subject9	90%	90%
Subject10	90%	90%
All Subjects	0%	45%

Table 1. Recognition accuracy of Fisher Linear Discriminant and SVM classification for 10 subjects

Knowing that SVM kernel choice is among the most important customizations that can be made when adjusting an SVM classifier to a particular application domain. It is interesting to test other kernel as: polynomial, sigmoid or gaussian radial basis function (RBF) and choose the best kernel in order to improve SVM recognition results.
Figures 8 and 9 present the results of the features signals separation. These features were projected down to a two dimensional space (Fisher features). Fisher transformation is often used to get a good representation of multidimensional class data in a two dimensional space. As expected, there were significant variations in the positions of data points for each emotion. The data are separated into well-defined clusters. Obviously, merging the features of all subjects does not refine the information related to target emotions (Figure 10). We can see that the data are unseparated, which explains the obtained Fisher rate as 0% for all subjects case (each emotion, varies widely across subjects).
Tables 2,3,4,5,6 and 7 give the confusion matrixes for the original training set of subject1, subject2 and all subjects, respectively, using Fisher discriminant and SVM method. It can be see, that the higher recognition ratio is always obtained for the corresponding and correct emotion for both methods, also, when we mixed the features signals. On the other hand, as it can be observed, the best results classification achievement was gained by the SVM method, especially, for all subjects case. These results are very promising in the sense that the application of Fisher linear discriminant analysis or SVM method to the task of emotion classification seems to provide very good results.

7. Conclusions and future works

in this paper we presented an approach to emotion recognition based on the processing of physiological signals. Physiological data was acquired in six different affective states and two pattern recognition methods have been tested: SVM method and Fisher linear discriminant. Recognition rates of about 90% were achieved for both classifiers. However, SVM classifier gives best results than Fisher discriminant using mixed features signals of different subjects. This study has shown that specific emotion pattern can be automatically recognized by a computer using physiological features.

Future work on arousal, valence assessment will be used in order to identify the emotion in the valence / arousal space. We intend to use wireless sensor in order to ensure a natural and without constraints interaction between human and machine. There is also much scope to improve our system to incorporate other means of emotion recognition. Currently we are working on a facial expression system which can be integrated with physiological signal features.

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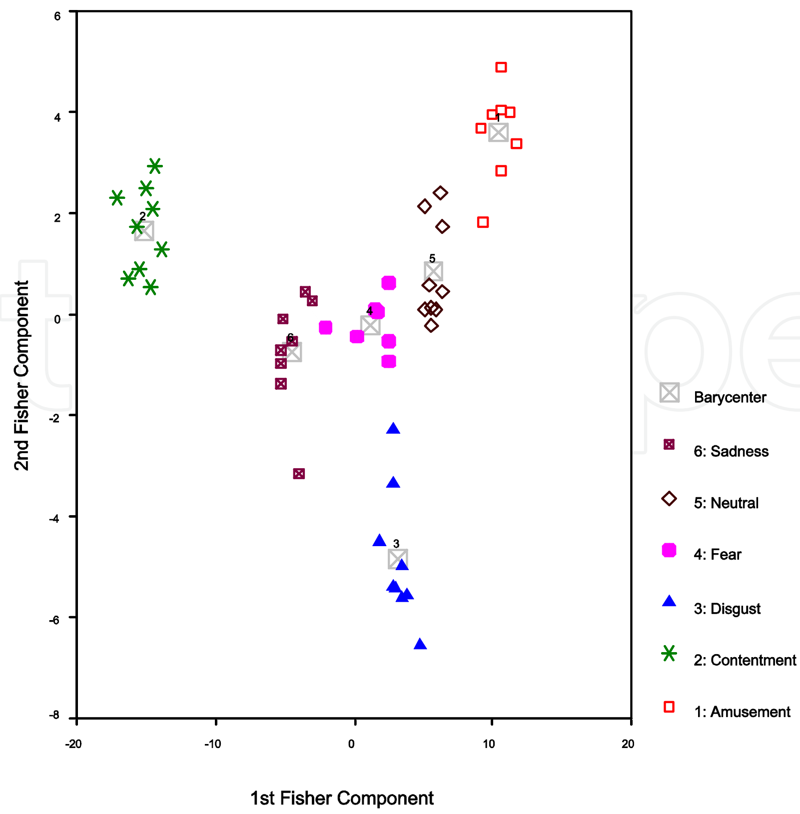


Fig. 8. Points representing emotion episodes are projected onto the first two Fisher features for subject!

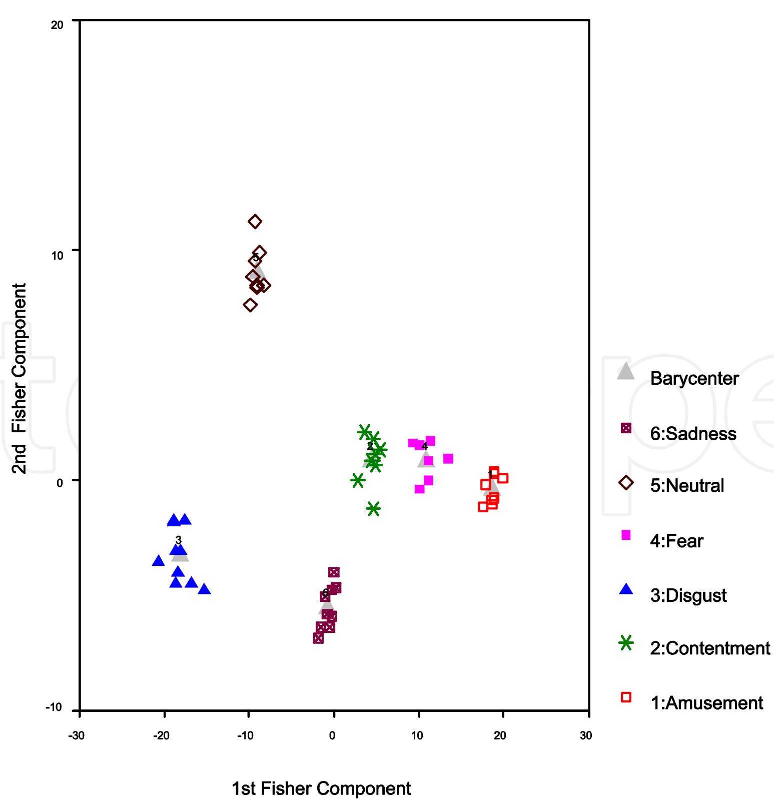


Fig. 9. Points representing emotion episodes are projected onto the first two Fisher features for subject2

Emotion	1	2	3	4	5	6
1	**65%**	0%	0%	10%	25%	0%
2	0%	**100%**	0%	0%	0%	0%
3	0%	0%	**100%**	0%	0%	0%
4	0%	0%	0%	**57.1%**	28.6%	14.3%
5	0%	0%	0%	0%	**100%**	0%
6	0%	0%	0%	12.5%	0%	**87.5%**

Table 2. Confusion matrix for emotion recognition using Fisher discriminant (subject1); 1: Amusement, 2: Contentment, 3: Disgust, 4: Fear, 5: Neutral, 6: Sadness

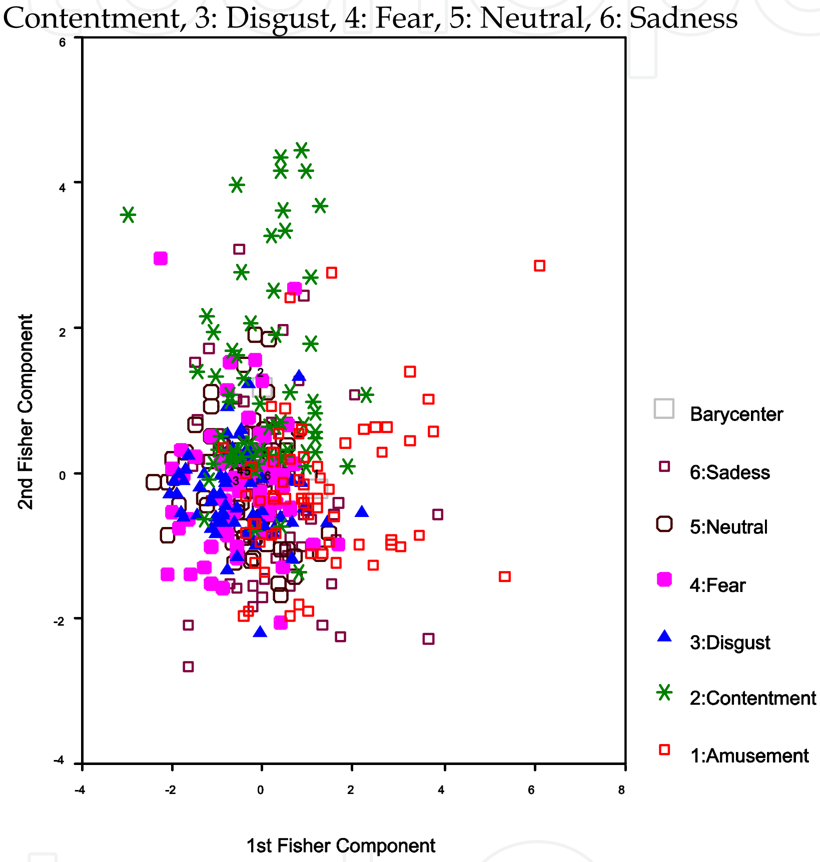


Fig. 10. Points representing emotion episodes are projected onto the first two Fisher features for all subjects

Emotion	1	2	3	4	5	6
1	**80%**	0%	0%	10%	10%	0%
2	0%	**90%**	0%	0%	0%	10%
3	0%	0%	**80%**	0%	10%	10%
4	0%	0%	0%	**80%**	10%	10%
5	0%	0%	0%	0%	**100%**	0%
6	0%	0%	0%	10%	40%	**50%**

Table 3. Confusion matrix for emotion recognition using SVM method (sub-ject1); 1: Amusement, 2: Contentment, 3: Disgust, 4: Fear, 5: Neutral, 6: Sadness

Emotion	1	2	3	4	5	6
1	**100%**	0%	0%	0%	0%	0%
2	0%	**87.5%**	0%	0%	0%	12.5%
3	0%	0%	**100%**	0%	0%	0%
4	14.3%	0%	0%	**85.7%**	0%	0%
5	0%	0%	0%	0%	**100%**	0%
6	0%	0%	0%	0%	0%	**100%**

Table 4. Confusion matrix for emotion recognition using Fisher discriminant (subject2); 1: Amusement, 2: Contentment, 3: Disgust, 4: Fear, 5: Neutral, 6: Sadness

Emotion	1	2	3	4	5	6
1	**90%**	0%	0%	0%	0%	10%
2	0%	**90%**	0%	0%	0%	10%
3	0%	0%	**100%**	0%	0%	0%
4	0%	0%	0%	**100%**	0%	0%
5	0%	0%	0%	20%	**80%**	0%
6	0%	0%	0%	20%	0%	**80%**

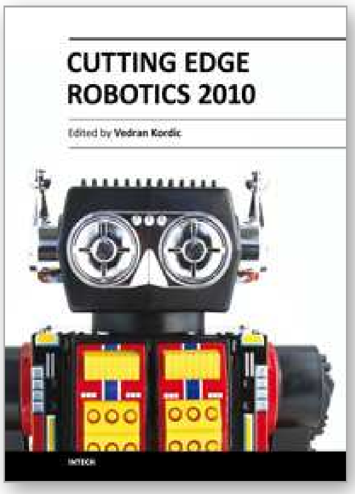
Table 5. Confusion matrix for emotion recognition using SVM (subject2); 1: Amusement, 2: Contentment, 3: Disgust, 4: Fear, 5: Neutral, 6: Sadness

Emotion	1	2	3	4	5	6
1	**35%**	5%	9%	4%	8%	5%
2	10%	**27%**	2%	9%	17%	1%
3	8%	3%	**35%**	6%	12%	0%
4	2%	5%	19%	**22%**	14%	5%
4	4%	4%	12%	12%	**29%**	6%
6	11%	10%	3%	7%	14%	**25%**

Table 6. Confusion matrix for emotion recognition using Fisher discriminant (all subjects); 1: Amusement, 2: Contentment, 3: Disgust, 4: Fear, 5: Neutral, 6: Sadness

Emotion	1	2	3	4	5	6
1	**46%**	4%	15%	1%	26%	8%
2	12%	**37%**	14%	4%	29%	4%
3	2%	6%	**59%**	5%	26%	2%
4	6%	7%	17%	**34%**	32%	4%
5	5%	10%	9%	3%	**69%**	4%
6	5%	11%	12%	6%	32%	**34%**

Table 7. Confusion matrix for emotion recognition using SVM (all subjects); 1: Amusement, 2: Contentment, 3: Disgust, 4: Fear, 5: Neutral, 6: Sadness



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